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Employment in the Great Recession: How Important Were Household Credit Supply Shocks?

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Abstract

I pool data from all large multimarket lenders in the U.S. to estimate how many of the over seven million jobs lost in the Great Recession can be explained by reductions in the supply of mortgage credit. I construct a mortgage credit supply instrument at the county level, the weighted average (by prerecession mortgage market shares) of liquidity-driven lender shocks during the recession. The reduction in mortgage supply explains about 15 percent of the employment decline. The job losses are concentrated in construction and finance.

JEL codes: E44, G21, R31

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1 Introduction

Employment fell by over 7 million in the Great Recession. Possible explanations include declines in credit supply (Eggertsson and Krugman 2012; Guerrieri and Lorenzoni 2017), household net worth (Mian and Sufi 2014; Giroud and Mueller 2015), and increases in uncertainty (Baker et al. 2016; Bloom 2014). The goal of this paper is to isolate and empirically assess the credit supply hypothesis: to what extent did reductions in credit supply play a causal and independent role in explaining the job losses that occurred in the period 2007-2010? To do so, I measure plausibly exogenous variation in credit supply (specifically for mortgages) at the county level, based on the interaction of prerecession county-lender market shares, which measure the importance of each lender to each locality immediately prior to the recession, and heterogeneous aggregate lender shocks during the recession. The county level estimates show that the reduction in mortgage supply negatively affected the health of residential markets, leading to declines in home buying, home prices, and employment in the construction sector; in other industries less directly linked to real estate, the job losses were much more muted and close to zero. A partial equilibrium aggregation exercise suggests that the decline in mortgage supply could explain close to 13 percent of the total job losses during the recession, or about 1 million of the total jobs lost.

The starting point of this paper is the observation that there is a strong OLS association between declines in local employment and mortgage credit issuance during the recession. This suggests that reductions in mortgage supply could have played an important role in driving the job losses. On the other hand, the OLS association could be entirely driven by reverse causality – declines in local employment and economic activity could have led to the decline in mortgage issuance. To isolate the effects of reductions in mortgage supply on economic activity, I construct a mortgage credit supply instrument at the county level.

The identification strategy exploits the well-known fact in the mortgage literature (discussed and further documented in the paper) that credit relationships in the mortgage market – as in the corporate market – are persistent and not easily substitutable.[1]

[1] Market shares at the county-lender level are highly persistent year on year; for example, 2005 county-lender shares explain 2007 shares almost 1-for-1. In the recession, there were few cases of lender entry into new localities: of 2008-2010 county-lender pairs, less than 8 percent were new. Even in 'normal' times there is limited shopping; mortgage borrowers tend to shop too little despite significant price dispersion for

The instrument measures the average supply response of a county's traditional lenders during the recession for 'nonlocal reasons' – reasons unrelated to the condition of local economies. The instrument is based on two sources of variation: (i) the heterogenous aggregate supply response of lenders during the recession, and (ii) variation in the reliance of localities to different lenders prior to the recession (measured with 2005-2007 market shares). To measure (i) aggregate differences in lender supply, I estimate lender fixed effects explaining variation in credit changes at the county-lender level during the recession, while holding constant local economic conditions (via county fixed effects). The lender fixed effects estimates are highly robust to alternative specifications, such as controlling for census tract fixed effects or loan characteristics varying at the county-lender level.[2] County-lender market shares (ii) come straight from the main data source, the Home Mortgage Disclosure Act. The county level credit supply instrument is the weighted average (by 2005-2007 market shares) of the lender fixed effects.

This paper is the first to construct a Bartik-style instrument based on the interaction of heterogeneous aggregate lender shocks and local market shares in the mortgage market during the recession. Working in parallel, Mondragon (2018) also studies the employment effects of household credit shocks during the recession, though his main instrument is based on county exposure to a single troubled lender during the recession (discussed shortly). My approach instead pools data from essentially all large multimarket lenders in the U.S., and follows in the tradition of recent related work studying the employment effects of reductions in *corporate* credit supply via Bartik-style instruments, such as Chodorow-Reich (2014), Greenstone et al. (2015), and Amiti and Weinstein (2018).[3] The main contribution of this paper is the focus on mortgage supply during the crisis, which may be particularly important, since mortgages are the largest category of private credit, and funding markets for mortgages were severely disrupted during the crisis. Notably, the private secondary market for mortgages fully collapsed at the onset of the crisis and remained inactive throughout. In line with

borrowers of similar characteristics (Alexandrov and Koulayev 2017; Woodward and Hall 2012; Lacko and Pappalardo 2010).

[2]Specifically, I regress credit changes at the county-lender level over 2007-2010 on county fixed effects and lender fixed effects in the baseline specification. The lender fixed effects are highly correlated (close to 1) when controlling instead for census tract fixed effects, using only high-income or low-income loans, and controlling for variation in precrisis county-lender loan characteristics.

[3]See Goldsmith-Pinkham et al. (2018) for a discussion of Bartik instruments.

previous research documenting that low liquidity contributed to lower credit issuance during the crisis (Ivashina and Scharfstein 2010; Cornett et al. 2011; Irani and Meisenzahl 2017), I document that mortgage lenders were more likely to cut supply if they relied on funding sources that proved fragile in the crisis. In particular, bank reliance on wholesale debt, loan sales in the secondary market, and loan sales to private buyers, explains 74 percent of the variation in lender supply during the recession (the lender fixed effects).

The 2SLS results controlling for a detailed set of county observables and region fixed effects are as follows. Declines in mortgage supply negatively affected the health of residential markets. For example, a supply-driven plausibly exogenous 10 percent decline in local mortgage issuance led to an 8 percent decline in new residential permits and a 7 percent decline in home prices. Areas with larger declines in mortgage supply also experienced higher default and foreclosure rates. The next question is whether the negative shock to real estate spilled over into local labor markets, both in directly related industries such as construction and in other industries.

The employment effects are largely direct and concentrated in construction and finance, a category of employment where about a third of workers are real estate intermediaries.[4] The main mechanism is that declines in mortgage supply reduce demand for housing, which contributes to job losses in industries reliant on housing demand. As evidence, I find that, for a given decline in mortgage credit, job losses in construction are larger in counties where housing supply is more elastic – areas where construction is more responsive to changes in housing demand. The estimated effects on other categories of employment – total private employment excluding construction and finance, and nontradable employment – are close to zero and not significant. The 2SLS estimates on these broad employment categories contrast with their OLS counterparts, which are 2-4 times larger and highly significant, suggesting the OLS estimates are biased upward due to reverse causality.

Overall, a 10 percent exogenous decline in local mortgage credit leads to a 1 percent decline in total private employment. To gain a sense of the aggregate implications of the county-level estimates, I perform a partial equilibrium aggregation exercise that exploits

[4]Construction and finance accounted for close to 35 percent of the job losses in the recession. Typically, their share in total employment is between 10-15 percent.

the in-sample distribution of the credit supply instrument, similar to the approaches in Chodorow-Reich (2014) and Mian and Sufi (2014). The exercise suggests reductions in supply could explain close to 13 percent of the total jobs lost, or about 1 million jobs. The bottom line is that the reduction in mortgage supply likely aggravated the fall in employment to a meaningful, but moderate, extent.

The main concern regarding instrument validity is that lender location might be correlated with unobserved local characteristics associated with job losses during the recession. Identification requires that below-average suppliers were not systematically sorted into localities experiencing below-average (or above-average) employment shocks. To the extent that counties and lenders are matched along observables, controlling for those characteristics isolates the remaining 'as good as random' variation in lender location. To that end, I control for a highly detailed set of local characteristics that explain about 60 percent of the variation in mortgage credit issuance across localities during the recession, including the share of subprime borrowers, the run-up in home prices during the boom, and various other demographic, housing, and industry characteristics. It is not possible to control for everything that may be relevant, however, and so I also rule out specific hypotheses about non-random lender location. For example, risky lenders may have moved to risky localities during the boom years. However, measuring the exposure of lenders to localities using 2000-2002 (instead of 2005-2007) market shares yields very similar results – the first-stage is weaker due to the loss in precision, but 2SLS point estimates are not statistically different. I also show that results are very similar when using region, division, or state fixed effects – this rules out hypotheses such as the possibility that weak suppliers in the recession were more heavily concentrated in the Sand States.[5]

This paper is part of the literature exploring the extent to which credit shocks explain the fall in employment in the Great Recession. Most empirical work focuses on the employment effects of corporate credit shocks.[6] Chodorow-Reich (2014) estimates that credit shocks explain between about one-fifth and one-third of the aggregate employment decline in the

[5]The results are robust to a number of checks including 'placebo' tests; controlling for the decline in small business lending in the recession; and the inclusion of large failed lenders (e.g., IndyMac) in the analysis.

[6]A related empirical literature studies the international transmission of the financial crisis through the banking sector (Cetorelli and Goldberg (2011); Haas and Lelyveld (2014); Schnabl (2012)).

year following the Lehman bankruptcy. Greenstone et al. (2015) find that credit shocks to small business loans help explain declines in borrowing, but produce only small employment effects. The credit supply variation I measure is specific to mortgages because county-lender market shares for mortgages and small business loans are largely uncorrelated – in other words, the mortgage lenders to one locality are often not the same as the small business loan lenders. The results in the paper are robust to controlling for declines in small business loans.

The most closely related paper is Mondragon (2018), whose credit supply instrument is exposure to Wachovia Bank, a troubled lender in the recession. He estimates that a 10 percent decline in instrumented mortgage credit leads to a 3 percent decline in employment, an elasticity two times as large as the OLS counterpart, and three times as large as my own estimate. One concern is potential 'bad' bank in a 'bad' region matching – Wachovia had a larger presence in states in the South Atlantic (e.g., FL, SC, NC) where job losses were among the worst in the country.

His estimates would have an upward bias if employment shocks and Wachovia location have correlated spatial fixed effects. In fact, when using division or state fixed effects, the Wachovia instrument significantly weakens. In contrast, my paper pools information from all large lenders located across the U.S. and employs a richer set of county controls, and so is more robust to potential concerns about non-random county-lender matching. For example, the 2SLS point estimates in this paper are essentially the same (not statistically different) when using region, division, or state fixed effects.

The paper is also related to the work of Mian and Sufi (2014), Mian et al. (2013), Kaplan et al. (2017), and others, on the household net worth channel, which assesses the hypothesis that declines in household net worth led to declines in aggregate demand and employment. The credit supply and household net worth channels are related – for example, the bursting of the housing boom helped precipitate the financial crisis. However, the run-up in house prices does not explain all of the ensuing economic decline. To isolate the credit supply channel, this paper asks: holding house prices constant, what were the employment effects of reductions in mortgage supply during the recession? I therefore condition on house price changes during the boom years, as well as various prerecession characteristics of localities associated with the housing boom and bust.

More broadly, this paper is part of the literature studying the effects of changes in mortgage supply on housing and labor markets. Most empirical work has focused on the former. Related work includes Favara and Imbs (2015); Mian and Sufi (2011); Adelino et al. (2012); Berrospide et al. (2016); Glancy (2015); Anenberg et al. (2016); Vojtech et al. (2016); Gropp et al. (2014); Gete and Reher (2016); Haltenhof et al. (2014); Chen et al. (2017). Only a handful of papers focus on the employment effects of reductions in mortgage supply. In the boom years, DiMaggio and Kermani (2016) use a federal preemption of national banks from local anti-predatory lending laws in 2004 to estimate the elasticity of nontradable employment with respect to mortgage supply. In the bust, Passmore and Sherlund (2016) find that counties more reliant on GSEs for mortgage credit experienced healthier labor markets in the Great Recession. I contribute to this literature by highlighting the heterogeneous industry effects of mortgage supply shocks on construction and financial employment.

2 Data Sources

I assemble a detailed county-level dataset including home prices, home sales, employment, mortgage credit, credit scores, demographics, borrower characteristics, industry composition, and various other local characteristics. The main source for mortgage data is the Home Mortgage Disclosure Act (HMDA). Mortgage lenders with offices in metropolitan areas are required to publicly disclose detailed information each year, including the dollar amount and number of mortgages issued, as well as the location (census tract, county) of the property securing the loan. Throughout the mid to late 2000s, HMDA covered over 90% of residential mortgage lending by dollar amount (Dell′Ariccia et al. 2012). I use mortgages for home purchase and improvement as the main measure (loan purpose 1 and 2 in HMDA). Figure 1 plots aggregate trends in mortgage originations, total private employment, and the S&P Case-Schiller U.S. National Home Price Index, with the series indexed to their 2006 value.

Data on home prices, permits, and delinquency and foreclosure rates are obtained from CoreLogic, the Census, and Black Knight McDash, respectively. For employment, I rely on two sources, both of which are establishment-based and provide nearly full coverage of private employment: the Quarterly Census of Employment and Wages (QCEW), and the County Business Patterns (CBP). I use the CBP to measure tradable and nontradable employment using the definitions in Mian and Sufi (2014), and the QCEW for the other employment data.

Table 1 shows summary statistics for over 1,000 of the largest counties in the U.S. Each of these localities had over 15,000 households in the 2000 Decennial Census and account for about 85% of aggregate employment. Table 2 provides definitions and sources for the data used throughout the paper. While mortgage credit declined over 2007-2010 in virtually all counties, there is significant cross-sectional variation in the decline, with credit falling by more than 53% in ten percent of the counties in the sample and falling by less than 25% in the top decile. Figure 2 shows there is a strong positive OLS association between declines in mortgage credit issuance and declines in both home prices and employment. This suggests that declines in mortgage issuance could have driven employment losses. On the other hand, the relationship might be entirely explained by reverse causality – declines in local economic activity could have driven the decline in employment and credit issuance.

I obtain lender-level data from HMDA, which provides loans by lender subsidiaries (respondents) and locality. I match subsidiaries belonging to the same parent company using the crosswalk maintained by Robert Avery, and aggregate to the level of the parent company (bank holding company, for banking institutions).[7] To calculate changes in lending at the lender level without including changes due to acquisitions, I use the standard approach (Bernanke and Lown 1991; Greenstone et al. 2015) of treating the acquired and acquiring institutions as part of the same entity throughout the sample period, which in this paper is over 2000-2010. I also conservatively drop failed institutions for most of the paper, because the extent to which their credit decline was supply- or demand-driven cannot be credibly estimated. Dropping these institutions is a conservative choice: it reduces the potential for biased estimates at the expense of statistical power. I show, however, that including the failed lenders, by assuming all of their credit decline was supply-driven and nonlocal, increases the explanatory power of the credit supply instrument, while leaving coefficient

[7] Available upon request at Robert.Avery@fhfa.gov

estimates in the second-stage essentially unchanged.

In measuring the exposure of counties to lenders, I focus on large multimarket lenders operating in multiple counties who did not file for bankruptcy during the crisis. Specifically, I include lenders operating in at least 100 counties in 2007, and who issued over $1 billion in mortgage originations in the same year. Table 3 gives a summary of lender-level statistics. The 57 lenders account for 75 percent of mortgage lending over 2005-2007, so they cover the majority of lending by market share, even though there were over 6,000 mortgage lenders in that period. I roll up the remaining small institutions into a single entity.

3 Differences in Lender Supply

There were substantial differences in supply across lenders during the recession. Some lenders almost fully halted originations, while a few even expanded. For example, mortgage originations fell by 69 percent at Citibank but increased by 17 percent at US Bank (Table 3). The empirical challenge, a variant of the reflection problem in Manski (1993), is that those differences could reflect borrower characteristics rather than differences in lender supply. For example, it is possible that US Bank's typical customers experienced above-average credit demand during the recession. The main empirical strategy is to estimate lender fixed effects explaining variation in credit changes during the recession, while holding various characteristics of loans constant including the location of the property via locality fixed effects; other work employing similar methods includes Khwaja and Mian (2008), Greenstone et al. (2015), and Amiti and Weinstein (2018). This strategy exploits the richness in the HMDA data which provides originations at the locality-lender level and includes various loan characteristics.

The lender fixed effects reveal substantial differences in aggregate supply across lenders. They are largely driven by differences in lenders' funding strategy: reliance on funding sources that proved fragile in the crisis, such as wholesale debt and private loan sales in the secondary market, explain close to 75 percent of the variation in lender supply. In contrast, credit growth in the boom years (2003-2006) does not help explain either differences in lender supply or credit growth over 2007-2010, as shown in Figure 3. Therefore, I interpret the supply differences as largely reflecting exposure to unexpected funding cost shocks during the recession.

Specifically, I estimate versions of the following linear model that specifies credit changes during the recession as a function of lender fixed effects, locality fixed effects, and lender-locality interaction effects:[8]

$$\Delta L_{i,b} = \alpha_i + \phi_b + \gamma D_{i,b} + \upsilon_{i,b} \tag{1}$$

where $\Delta L_{i,b}$ are percent changes in mortgage credit originations at the county-lender level over 2007-2010; α_i are locality fixed effects (county or census-tract); ϕ_b are lender fixed effects; and $D_{i,b}$ are prerecession county-lender characteristics. The parameters of interest are those associated with the vector of lender fixed effects ϕ_b, which capture the idiosyncratic lender factor common across localities explaining variation in credit changes, net of locality fixed effects and prerecession county-lender characteristics.

The model captures many of the reasons for variation in credit changes at the lender-locality level during the Great Recession. For example, if originations to a locality declined sharply because of deteriorating local economic conditions – declines in local productivity, house prices, or credit scores – that will be captured by the locality fixed effects α_i. Similarly, if originations decline because it is difficult for lenders to fund new mortgages, that would be captured in the lender fixed effects ϕ_b. It is also possible that the variation is driven by interaction effects $D_{i,b}$ – for instance, Citibank's traditional borrowers could have tended to experience below-average credit demand shocks, even within localities.

In the baseline specification, I control only for county fixed effects. In this case the identifying assumption is that within-county credit demand shocks are uncorrelated with lender shocks. For example, supply contractions for Citibank would be overestimated if their borrowers tend to be low-income, and low-income borrowers experienced worse credit demand shocks than average, even within-counties. To address this possibility, I estimate equation 1 using only high income loans, but estimates are very similar. Specifically, I estimate equation

[8] The lender fixed effects are estimated using 30,161 county-lender observations, for the 57 lenders in the sample, and for county-lender pairs where the dollar value of originations is larger than \$1 million. The lender fixed effects explain about a fifth of the variation in within-county lending changes over 2007-2010.

1 using only loans to borrowers with income over \$70,000 the median income of borrowers in 2007. The correlation coefficient between the lender fixed effects estimates in the baseline and the specification with only high income loans is 0.96; see Figure 4. When using only low-income loans (borrower income below \$70,000), the correlation coefficient is also high, 0.94.

I also estimate equation 1 using census tract fixed effects rather than county fixed effects. Census tracts are statistical subdivisions of counties, each generally having a population size between 1,200 and 8,000 people. Census tracts are smaller and are more homogeneous than counties.[9] The lender fixed effects estimates when using census tract fixed effects are also highly correlated with the baseline (0.91). This shows that using a more detailed local control for changes in credit demand has very little bearing on the lender fixed effects estimates. Another alternative is to directly control for differences in the prerecession profile of borrowers and lenders via county-lender characteristics $D_{i,b}$. The county-lender characteristics observed in HMDA are borrower income, fraction of loans classified as being high-risk, race, type of loan (owner-occupier), and credit growth in the peak boom years 2003-2006 by county-lender. When including $D_{i,b}$ in equation 1, the lender fixed effects estimates are again highly correlated.

Table 4 shows sample statistics for the 25 largest lenders in the sample. Column 2 provides percent changes in national mortgage originations over 2007-2010, and Column 3 ranks them by percent changes in mortgage originations. Column 4 ranks lenders by the lender fixed effects estimates; above-average lender fixed effects indicate above-average supply. Changes in the ranking (going from Column 3 to 4) indicate differences in the degree to which national changes in mortgage originations were driven by geographic variation in exposure to credit demand shocks. For example, the drop in Flagstar's ranking from 8^{th} to 14^{th} (from Column 1 to Column 2) indicates that lending changes for this bank remained relatively robust in the recession partly because of its exposure to above-average geographies (in this case the Midwest). Conversely, the improvement in the ranking of JPMorgan Chase

[9] I rank census tracts within a county by borrower income, and divide the census tracts into four equal-sized groups by income, i.e. the top quartile consists of the high-income census tracts in the county. Census tract-income groups are more homogeneous than the county – in 2007, the median within-group standard deviation of HMDA borrowers in the census tract-income groups was \$92 thousand, 27% lower than in counties.

from 52^{th} to 35^{th} indicates that part of its national decline in originations was driven by exposure to underperforming areas. While there are some changes, overall the rankings are highly correlated (correlation coefficient = 0.89), indicating that the lender fixed effects are only weakly correlated with locality fixed effects.

3.1 Funding Fragility and Differences in Supply

What explains the dispersion in aggregate supply across lenders, the variation in the lender fixed effects ϕ_b? In line with previous research documenting that low liquidity contributed to lower credit issuance during the crisis (Ivashina and Scharfstein 2010; Cornett et al. 2011; Brunnermeier 2008; Gorton and Metrick 2012; Kacperczyk and Schnabl 2010; Ramcharan et al. 2016), this section shows mortgage lenders were more likely to cut supply during the recession if they relied on funding sources that proved fragile in the crisis. As discussed in Passmore et al. (2005), mortgage loans can usually be funded in one of three ways: (i) via loan sales in the secondary market, or through balance sheet retention; (ii) if kept in the balance sheet, through wholesale debt or deposit-like liabilities; (iii) if sold in the secondary market, through loan sales to the GSEs (e.g. Fannie Mae, Freddie Mac, Ginnie Mae), or through sales to private buyers. I measure each of these three funding strategies by combining lender data from HMDA and the Federal Reserve's FRY-9C.

Table 5 reports results from regressions of differences in lender supply (ϕ_b) against differences in funding strategy over 2006-2007 (see also Figure 5) for the banks in the sample. Specifically, I regress the lender fixed effects on the precrisis ratios of wholesale debt to assets, loan sales to total originations, and private loan sales to total loan sales. These measure the reliance prior to the crisis of banks on wholesale debt and the originate-to-distribute lending model. Column 1 shows variation in these three funding strategies explain 74 percent of the variation in supply differences ϕ_b.[10] Column 2 shows that lower prerecession capital ratios are also associated with declines in credit supply, though this factor is relatively minor, judging by its 3 percentage point contribution to the R-squared (Column 2). Column 3 shows

[10]In complementary work, Dagher and Kazimov (2012) find that mortgage lenders more reliant on wholesale funding were more likely to reject mortgage applications during the recession, after controlling for various borrower characteristics.

that, in contrast, prerecession credit growth (over 2003-2006) is not helpful in explaining variation in differences in supply during the Great Recession. Observations are weighted by the dollar amount of mortgage originations in 2007, although the weighting is not critical, as shown in Column 4.

I measure bank-level exposure to wholesale funding as the ratio of non-core funding (sum of large time deposits, foreign deposits, repo sold, other borrowed money, subordinated debt, and federal funds purchased) to total assets, from the Federal Reserve's FRY-9C form, a standard definition in the literature (Irani and Meisenzahl 2017). To measure lender exposure to the secondary market, I use data from HMDA, which provides loan sales in the secondary market by year and type of buyer. Reliance on loan sales is measured as the share of loans originated and sold to total originations over 2005-2007. Exposure to private securitization is measured as the ratio of private investor loan sales to total loan sales over 2005-2007.[11]

Measuring reliance on loan sales to private buyers is important since private-label residential mortgage securitization, which funded about 30% of mortgages over 2005-2007, went to essentially zero in 2008-2010 (Frame et al. 2015); see also Avery et al. (2011), and Nadauld and Sherlund (2009)). Because private investors stopped purchasing nongovernment-insured mortgages, lenders reliant on those sales likely cut supply during 2008-2010. For example, Calem et al. (2013) find that banks who were pre-recession more dependent on loan sales experienced more severe declines in jumbo lending, which are loans too large to be purchased by GSEs, and thus can only be sold to private investors, during the recession.

Loan sales to GSEs also became more expensive. G-fees, the monthly insurance fee GSEs charge as a fixed fraction of the loan balance, increased from about 20 basis points in 2005-2007 to 30 basis points in 2008-2010 (Fuster et al. 2013). Putback risk also increased in 2008. Lenders are required to repurchase loans sold to GSEs if it is found that those loans fail to satisfy original underwriting standards. While putbacks were rare, they rose during the recession, with Fannie Mae estimating that 3.7 percent of single-family loans purchased over 2005-2008 were putback to lenders, whereas the figure in other periods tended to be

[11] Private loan sales are defined as loan sales to any buyers excluding FNMA, FAMC, GNMA, FHLMC, and lender affiliates.

less than 0.5 percent[12]

4 The Nonlocal Lending Shock

Differences in lender supply affected counties differently, because of variation in the intensity of preexisting county-lender relationships, as measured by market shares prior to the recession. The credit supply instrument – the nonlocal lending shock – is the weighted average, for county i, of lender supply shocks in the recession ϕ_b (from equation 1). The weights are county-lender 2005-2007 mortgage origination market shares. The sum is taken over all large multimarket lenders in the sample B, as discussed in section 2:

$$Nonlocal\ Lending\ Shock_i = \sum_B Share_{i,b}\phi_b \tag{2}$$

Counties had below-average access to mortgage credit, all else equal, if they had existing relationships (as measured by 2005-2007 market shares) with lenders with below-average supply in the recession. New lender entry would work towards offsetting the decline in credit supply by the locality's traditional lenders. In the extreme case of perfectly substitutability, lender entry would fully offset the reduction in supply by the locality's traditional lenders.

The instrument, however, is not weak with the first-stage Kleibergen-Paap F statistic in the baseline over 40. I provide evidence of both highly persistent county-lender relations prior to the crisis, and of limited new lender entry during the recession. First, county-lender market shares are highly persistent year-on-year. Table 6 shows results from regressing 2007 county-lender market shares on 2005 shares. Column 1 shows that 2005 shares explain 91 percent of the variation in 2007 shares, with the coefficient on the 2005 shares equal to 0.92. The left panel of Figure 6 plots 2007 shares against 2005 shares. Moreover, the relationship between 2005 and 2007 shares is highly stable across localities. The correlation coefficient and R-squared are very similar when focusing only on high credit score counties or only low credit score counties (Columns 2 and 3), or when using county fixed effects (Column 4). The persistence in credit relationship extends to at least the early 2000s. The right panel

[12]source: Fannie Mae 10-K 2013, p. 143

in Figure 6 plots 2000 market shares against 2007 market shares; there is a strong positive association, with 2000 shares explaining 71 percent of the variation in 2007 shares.

As for limited entry, I find few cases of lenders entering new counties in the recession: of all county-lender pairs in 2008-2010, only 7.85% were new matchings. The lack of entry suggests substantial switching costs across lenders during the recession. Part of the reason for low new entry may be that only a handful of lenders were expanding during the recession. Because most lenders were contracting, they may not have been looking to expand into new localities.[13] The contraction in lending by many mortgage lenders, particularly the larger ones, is also documented in Gete and Reher (2016) and Chen et al. (2017).

The findings in this paper on persistent credit relationships and limited entry during the recession are in line with the literature documenting stickiness in mortgage credit relationships and limited shopping in the mortgage market in spite of significant price dispersion. In a survey of recent mortgage borrowers, Alexandrov and Koulayev (2017) report that close to half of the borrowers did not do any shopping. Woodward and Hall (2012) also find that borrowers engage in too little shopping, and "sacrifice at least $1,000 by shopping from too few brokers." Lacko and Pappalardo (2010) shows that mortgage borrowers are often severely uninformed about key costs associated with getting a mortgage, with half of respondents having problems identifying the loan amount, and two-thirds being unaware of prepayment penalties, for example. Moreover, Mondragon (2018) and Nguyen (2014) find evidence for stickiness in the mortgage market, in line with the large literature showing substantial switching costs for firms, as recently discussed in Chodorow-Reich (2014).

The main concern with instrument validity is that the credit supply instrument, county exposure to lender supply shocks, may be correlated with unobserved characteristics of counties affecting employment. It would be sufficient (but not necessary) if lender location is randomly distributed across counties. That is unlikely to be the case, however. Below-average suppliers in the recession may have been more likely to locate in subprime counties (for example) prior to the crisis. To the extent I can observe and control for the fraction of subprime borrowers (and other relevant local characteristics), I can isolate the 'as good as random' variation in lender location. To that end, I employ a detailed set of prerecession

[13] These statistics are based on the 57 lenders in the sample as described in section 2.

county characteristics, including the subprime share, that explains close to 60 percent of the cross-sectional variation in mortgage credit changes over 2007-2010, described in Table 2. The controls include: 2006 household debt to income used in Mian and Sufi (2009); the run-up in house prices over 2003-2006; the fraction of subprime borrowers in 2006; industry composition such as the construction share of employment in 2006; loan characteristics such as local incidence of FHA or investor loan over 2003-2006; demographics; and measures of local lending competitiveness.[14] Figure 7 is a map of the nonlocal lending shock, after controlling for a detailed set of county covariates. The map appears balanced with no apparent trends by region.

Conditional on the detailed set of county observables used in the paper, I find evidence consistent with 'as good as random' county-lender matching both in the boom and before. The results in the paper are robust to measuring county exposure to lender shocks using 2000-2002 shares (instead of 2005-2007 shares). This addresses the concern that risky lenders may have located in risky counties during the housing boom. As for potential non-random county-lender matching before the 2000s, I estimate the models using different regional fixed effects, including state, division, and region fixed effects; substantially different estimates would be evidence of correlated fixed effects at regional levels for employment outcomes and lender location i.e., regional county-lender matching. However, estimates are consistent across specifications. As discussed shortly, I perform various other checks that find support for the exclusion restriction, including 'placebo' tests; controlling for declines in small business lending in the recession; and the inclusion of large, failed lenders (e.g. IndyMac) in the analysis.

[14] Previous literature has established that different household characteristics are associated with the severity of the housing boom and bust. For the incidence in subprime lending, see: Keys et al. (2010),Demyanyk and Hemert (2011), Dell'Ariccia et al. (2012), Gerardi et al. (2008), and Mian and Sufi (2009). For the growth in household debt to income, see: Mian and Sufi (2014), and Carroll and Kimball (1996). For demographics: Elsby et al. (2010). For loan characteristics: Haughwout et al. 2011; Chinco and Mayer 2016; Bhutta 2015; Bhutta and Ringo 2014

5 Empirical Framework and Results

I now discuss results based on the following 2SLS specification:

$$\Delta Outcome_i^j = \theta X_i + \beta \Delta \widehat{Credit}_i + f_s + \epsilon_i \tag{3}$$

$$\Delta Credit_i = \delta X_i + \rho Nonlocal\ Lending\ Shock_i + f_s + v_i \tag{4}$$

where observations are at the county i level; changes are over 2007-2010 for different outcome variables j (house sales, house prices, employment) each estimated separately; and f_s are fixed effects that could be at the region, division, or state level – I report results for each. Table 2 defines the set of prerecession county controls X_i as well as the outcome variables. The nonlocal lending shock is the credit supply instrument defined in equation 2. All of the outcome variables are expressed as percent changes over 2007-2010. For employment categories and the home price index, changes are taken between 2007Q4 and 2010Q4. For mortgage credit (a flow) changes are taken between the average dollar flow over 2008-2010 with respect to the value in 2007.[15] Mortgage flows are deflated using the GDP deflator.[16]

I use data on approximately the largest 1,000 counties in the U.S. (those having over 15,000 households in the 2000 Decennial Census), which account for 85% of aggregate employment. I drop states having 3 or fewer counties, to have at least a few observations per state for the specifications that use state fixed effects. Observations are weighted by the number of households in the 2000 Decennial Census, though results are very similar without weighting.[17] Extreme observations (1% from each tail) are dropped from each dependent variable.[18] Standard errors are clustered at the division level to allow for correlated shocks within broad geographic regions due to, for example, state or division-specific institutional

[15]Using 2005-2007 as the base period produces nearly identical results, for example, the correlation coefficient between $\Delta Credit_i$ using 2007 as the base period and using 2005-2007 as the base is $\rho = .87$. Table 10 in the Online Appendix reports the main estimation results using 2005-2007 as the base.

[16]Alternatively, $\Delta Credit_i$ could be defined as the percent change in the number of mortgage originations, with very similar results; Table 11 in the Online Appendix shows the main 2SLS results when doing so.

[17]Table 12 in the Online Appendix reports unweighted results for counties with over 40,000 households in the 2000 Decennial Census – these close to 500 counties account for 76% of total employment.

[18]For example, I drop house price growth outliers from the house price regression, but I don't drop those counties from the private employment growth regression (unless they are also outliers in that variable). The only exception is growth in house permits for which I winsorize 5% of observations.

arrangements and spatial correlation.[19] Estimates are robust to alternatives, such as clustering at the commuting zone level (Table 13 in the Online Appendix).

5.1 First Stage Results

The nonlocal lending shock has significant independent explanatory power over local changes in mortgage credit in the Great Recession, consistent with high switching costs across lenders. Table 7 reports first-stage regression results; all the controls listed in Table 2 are included (e.g. the share of subprime borrowers, measures of the severity of the housing boom, and various demographic, industry, and loan characteristics) though only the nonlocal lending shock coefficient estimates are reported, to economize on space. Columns 1-4 include varying degrees of spatial fixed effects, ranging from no spatial fixed effects (Column 1) to region, division, and state fixed effects specifications (Columns 2-4 respectively). The R-squared is reasonably high in all specifications (55 percent or higher), indicating that the regression controls are helpful in explaining variation in mortgage credit issuance. Across specifications, the coefficient estimate on the instrument is positive and strongly significant. For example, in the specification without spatial fixed effects (Column 1), a 10 percent reduction in the nonlocal lending shock is associated with a 4.79 percent decline in mortgage credit issuance; the first-stage Kleibergen-Paap F statistic is slightly above 20.

The instrument has considerably explanatory power in all models with different spatial fixed effects. The F statistic, with degrees of freedom adjusted for division level clustering, is over 10 in all the specifications, a rule of thumb commonly used to indicate weak instrument problems (Stock and Yogo 2002). The F statistic is lowest in the specifications with state fixed effects (13.95), since this specification uses less information (only within-state variation in the instrument). In some models with state fixed effects, such as in the residential permits model (Table 1, Column 4 of the Online Appendix), the first stage F statistic is just above 10. I report in the Online Appendix p-values for LM tests of underidentification based on the Kleibergen-Paap rk statistic; the null of underidentification can be rejected at the 5% significance level across all models including those with state fixed effects.

[19] The Census divides the US into 9 divisions – New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

5.2 Effects of Supply Reductions on Residential Markets

Supply-driven, exogenous declines in mortgage credit are statistically associated with declines in home sales, home prices, and increases in delinquency rates as well as foreclosure rates. This is evidence of the negative effects of declines in mortgage supply on the health of local housing markets. The mechanism is that reductions in mortgage supply reduce the ability of households to buy homes and to refinance. Table 8 reports two stage least squares results for different housing market outcomes in the models with region fixed effects and standard errors clustered at the division level. I use region fixed effects in the baseline, though I provide results with other spatial fixed effects in the Online Appendix and in some cases throughout the paper.

Declines in credit supply are associated with declines in home permit issuance. Column 1 shows that a 10 percent reduction in mortgage credit (when instrumented using the nonlocal lending shock) is associated with a 8.24 percent decline in the issuance of new residential permits – close to a one-to-one effect. This is evidence that households were unable to offset the reduction in credit availability originating from nonlocal sources by borrowing from private sources or from lenders other than their traditional, prerecession lenders. The effect operates through the extensive margin – fewer loans were taken out, which led to lower housing demand and caused declines in new permits. The effect is very similar (8.55 percent decline) when measuring changes in mortgage credit using declines in the number of loans, rather than in the real dollar value, as reported in Table 11 of the Online Appendix. Declines in mortgage credit are also associated with declines in home prices. A plausibly exogenous 10 percent decline in mortgage credit is associated with a 7.35 percent decline in home prices.[20]

Delinquency rates and foreclosure rates also increased more in counties with below-average supply. Table 8 shows that a 10 percent decline in mortgage credit is associated with 1.42 and 0.87 percentage point increases in delinquency and foreclosure rates. This is evidence of the contractionary effects of reductions in mortgage supply on the health of local

[20] This is consistent with other articles finding that supply-driven changes in credit have real effects on home prices, such as Favara and Imbs (2015), Mian and Sufi (2011), Adelino et al. (2012), Favara and Imbs (2015), DiMaggio and Kermani (2016), Anenberg et al. (2016), Vojtech et al. (2016), Passmore and Sherlund (2016), and Kung (2015).

housing markets. The fall in home prices induced by the credit shock would make it more likely for households to go underwater.

In the Online Appendix I present results for the each dependent variable with no fixed effects, region, division, or state fixed effects. The main conclusions are essentially the same. The point estimates are very similar. For example, a 10 percent reduction in mortgage credit is associated with a 6.73, 7.57, 8.28, and 7.98 percent decline in home prices in the models without spatial fixed effects, and with region, division, and state fixed effects respectively (Table 2 of the Online Appendix).

5.3 Effects of Supply Reductions on Employment

Declines in mortgage supply contributed to the job losses in the recession, though to a moderate extent. The job losses explained by the mortgage shock are concentrated in construction and financial services, a category of employment where over a third of workers are real estate intermediaries. The likely mechanism is that reductions in supply caused declines in housing demand, which negatively affected employment in industries reliant on housing demand. As evidence for this, I find that the construction losses are stronger in areas where housing supply is more elastic, that is, in areas where construction responds more to changes in housing demand. Overall, a supply-driven plausibly exogenous decline in mortgage credit issuance is associated with about a 1 percent decline in total private employment. Using the in-sample variation of the nonlocal lending shock, I estimate that about 15 percent of the aggregate employment losses in the Great Recession can be explained by declines in mortgage supply.

Weak mortgage supply contributed to job losses in the construction sector. Table 9 shows that a 10 percent decline in mortgage credit originating from nonlocal sources is associated with a 3.81 percent decline in construction employment for the model with region fixed effects, with point estimates similar for the other specifications. The mechanism is that declines in mortgage supply reduce housing demand, which is associated with lower employment in construction.

The employment losses in construction were, for a given decline in instrumented credit, more severe in areas where housing supply is more elastic.[21] That is, in areas where con-

[21] I add the interaction of credit changes and the housing supply elasticity to the regression model with

struction responds more strongly to changes in housing demand, the employment effects of a given credit decline were stronger. To see this, I focus on the sample of counties for which the Saiz (2010) measure of the elasticity of housing supply is available.[22] Table 10 reports results for changes in home permits for new construction and construction employment for the model with region fixed effects. The coefficient estimate is positive for the interaction of credit changes and housing supply elasticity and significant at the 1% level for construction employment (Column 2). For the permits model (Column 4), the interaction is also positive and significant at the 10% level. That is, the same relative decrease (increase) in credit is associated with lower (higher) permit issuance and construction employment in areas with higher housing supply elasticities. This is evidence for the mechanism that reductions in mortgage supply reduced housing demand and contributed to employment losses in construction.

Declines in mortgage supply also caused job losses in finance. Table 9 shows that a 10 percent reduction in mortgage credit is associated with a 4.40 percent decline in employment in financial services in the model with region fixed effects. The likely mechanism again is that reductions in supply negatively affected housing demand, and therefore demand for housing intermediaries.

Via the effects on construction and financial employment, declines in mortgage credit led to declines in total private employment. Table 9 shows two stage least squares results for different employment categories, including total private employment. Column 3 shows that a 10 percent reduction in mortgage credit originating from nonlocal sources is associated with a significant 1.14 percent decline in total private employment. The models with other types of spatial fixed effects have similar point estimates, as reported in Table 7 of the Online Appendix, though confidence intervals are wider especially when state fixed effects are used, since these models use less information (only within-state variation). In the specification with state fixed effects, for example, a 10 percent reduction in instrumented mortgage credit is associated with a (not significant) 8.3 percent decline in employment. The Online Appendix

region fixed effects. For the two endogenous regressors (credit changes and the interaction of credit changes and the housing supply elasticitiy), I use two instruments – the nonlocal lending shock, and the interaction of the nonlocal lending shock with the housing supply elasticity.

[22] Saiz (2010) estimates housing supply elasticity as a nonlinear combination of data on physical and regulatory building constraints and population levels in 2000 at the metro area level.

reports estimates for all of the dependent variables discussed in the paper for specifications with no spatial fixed effects, region, division, and state fixed effects.

Declines in mortgage supply are only weakly associated with declines in employment in other, broader employment categories – 'other employment' (total private excluding construction and finance) and nontradable employment, which mostly consists of local retail and food. These are shown in Table 9, Columns 4 and 5 respectively. The coefficient estimates are close to zero and not significant. That is, the negative shock on local real estate markets did not appear to significantly spillover to broader local employment categories. One possibility is that the real estate shock did have large spillover effects, but that those effects were nonlocal, and were instead dispersed through localities through the tradable sector. However, there is little evidence that the local real estate shock had large spillover effects on the local nontradable sector (Column 5). In Boldrin et al. (2012) the spillover between a housing shock to the rest of the economy depends on the elasticity of substitution between consumption and housing. The results in this paper suggest the (local) elasticity is relatively low.

The elasticity estimates of other and nontradable employment also contrast with their OLS counterparts, which are about twice as large and strongly significant, with t-statistics ranging from 3 to 8 across specifications, as shown in Table 11. That the OLS coefficients are larger suggests that they are biased upward, due to reverse causality – employment losses may lead to declines in mortgage issuance. The credit supply instrument is strong, and helps predict declines in real estate activity, such as declines in home permits, home prices, and construction employment. But it does not help explain substantial job losses in industries less directly related to real estate. This ameliorates concerns about reverse causality – if local employment shocks were correlated with the instrument, then the 2SLS estimates for broad employment categories would likely be large and significant.

In parallel work Mondragon (2018) also estimates the county level elasticity of employment with respect to mortgage supply during the recession. We both find that reductions in mortgage supply mattered for employment in the recession, though the estimated effects in Mondragon (2018) are substantially higher. He estimates that a 10 percent decline in instrumented mortgage credit is associated with a 3 percent decline in employment, an elasticity about two times as large as the OLS counterpart, and three times as large as my own estimate.[23] The main difference between the papers is the credit supply instrument; his instrument is prerecession exposure to Wachovia Bank, a troubled lender acquired by Wells Fargo in late 2008.[24] One reason his estimates are likely larger is 'bad' bank in a 'bad' region matching – Wachovia had a larger presence in states in the South Atlantic such as Florida, South Carolina, and North Carolina where job losses were among the worst in the country.

The Wachovia instrument significantly weakens when controlling for characteristics of localities correlated with both Wachovia location and employment losses during the recession. For example, using only division or state fixed effects greatly diminishes the statistical power of the Wachovia instrument. To see this, I obtain Wachovia 2005-2006 purchase shares from HMDA and restrict the sample to counties in the South and East. The first-stage F statistic associated with the Wachovia instrument is 14.47, absent other controls including regional fixed effects. When including division (state) fixed effects, the F statistic drops to 4.33 (0.93).[25] In contrast, the results in my paper are very similar when using no fixed effects, or region, division, or state fixed effects. Moreover, it is not the case that the results are different because Wachovia was a particularly troubled lender. In fact, Wachovia was acquired by Wells Fargo, the strongest lender of the top 4. As discussed shortly, the results in this paper are very similar even when including large, failed lenders in the analysis such as IndyMac, which was not rescued by another institution.

5.4 Aggregate Implications

Overall, I find that reductions in mortgage supply could explain close to close to 13 percent of the employment losses in the U.S. over 2007-2010, or about 1 million of the jobs lost. This is evidence that reductions in mortgage supply mattered for employment. The imputation is based on a partial equilibrium aggregation exercise that answers the counterfactual ques-

[23]These estimates replicate the earlier Mondragon (2014). In more recent versions, changes in Mondragon's specifications such as variable standardization and sample restrictions make replicating Mondragon (2018) less straightforward.

[24]Mondragon (2018) continues to use Wachovia as the key source of identification as in earlier versions (Mondragon 2014), though the more recent version uses a few other regional lenders as a robustness check.

[25]Observations are weighted by population in 2007, and standard errors are clustered by state. These results are available upon request.

tion: what if counties, all else equal, had experienced the best credit shock in the sample – specifically, the credit shock of the counties in the top 5 percent of the distribution? The improvement in supply generates employment gains via the estimated elasticity of employment with respect to mortgage supply. This approach addresses the challenge that the level effect of supply reductions cannot be recovered from the cross-section by assuming that the top percentile of counties by the credit supply instrument represent a 'no credit shock' scenario. This is a standard aggregation exercise in this literature, with similar approaches in Chodorow-Reich (2014) and Mian and Sufi (2014). The estimate would be biased downwards if the top percentile counties also experienced a reduction in supply. The severe disruptions in mortgage supply in the recession affecting wholesale funding markets and loan sales in the secondary market suggest the assumption is conservative.

First, define the counterfactual employment change in county i, ΔEmp_i^{cf}, as the predicted employment if county i had experienced the nonlocal lending shock of county zero (NLS_0), rather than its own (NLS_i), after conditioning on all other observables X_i:

$$\begin{aligned}\Delta Emp_i^{cf} =& E[\Delta Emp_i | NLS_i = NLS_0, X_i] \\ =& \Delta\widehat{Emp}_i + \beta(\Delta\widehat{Credit}_i(NLS_0) - \Delta\widehat{Credit}_i(NLS_i)) \\ =& \Delta\widehat{Emp_i} + \beta\rho(NLS_0 - NLS_i)\end{aligned}$$

where $\Delta\widehat{Emp_i}$ denotes the fitted value from the private employment regression model with region fixed effects, β is the estimated elasticity of employment with respect to mortgage supply, and ρ is the coefficient on the nonlocal lending shock in the first-stage regression. I then recover the end-period levels of employment corresponding to both the counterfactual and fitted changes in employment, using the initial-period employment level: $Emp_{i,2010Q4}^{cf} = Emp_{i,2007Q4}(1 + \Delta Emp_i^{cf})$ and $\widehat{Emp}_{i,2010Q4} = Emp_{i,2007Q4}(1 + \Delta\widehat{Emp}_i)$. Then, the total job loss explained by variation in the nonlocal lending shock is given by:

$$\textit{Total jobs lost explained by lending shock} = \sum_{i:NLS_i < NLS_0} [Emp_{i,2010Q4}^{cf} - \widehat{Emp}_{i,2010Q4}] \quad (5)$$

The fraction of jobs lost that is explained by the lending shock is given by:

$$\frac{\sum_{i:NLS_i<NLS_0}[Emp^{cf}_{i,2010Q4} - \widehat{Emp}_{i,2010Q4}]}{\sum_{i:NLS_i<NLS_0}[Emp_{i,2010Q4} - Emp_{i,2007Q4}]} \tag{6}$$

The exercise indicates that the decline in mortgage supply can explain about 13 percent of the employment losses in the Great Recession, when defining county zero as the 95th percentile county by the credit supply instrument, and using the coefficient point estimate $\beta = 0.114$ from the region fixed effects model. There is uncertainty around β, however. For example, $\beta = 0.083$ in the model with state fixed effects. Using the latter, the aggregation exercise suggests the mortgage credit supply shock explains about 9 percent of the job losses during the recession. Alternatively, the 95 percent confidence interval for β in the region fixed effects specification ranges from 0.048 to 0.179; using this range, the decline in mortgage supply explains between 4 and 22 percent of the job losses during the recession.

Another important parameter choice is which counties are used as the 'no credit shock' reference. The baseline uses the 95th percentile as the baseline. If localities in the top 5 percent of the credit supply distribution also experienced a reduction in credit supply, the aggregation exercise will deliver an under-estimate. When using the top 1 percent as a reference instead, the aggregation exercise suggests declines in mortgage supply can explain 19 percent of the job losses in the recession.

The bottom line of these aggregation exercises is that the reduction in mortgage supply likely aggravated the job loss during the recession, though moderately so. 13 percent of the total job losses is sizable – about 1 million jobs lost is hardly small – but it is far from the bulk of the job losses, as argued by Mondragon (2018) and particularly Mondragon (2014) which attributed about 60 percent of the total job losses (at a minimum) to household credit supply shocks. In sum, the evidence in this paper adds nuance to the debate of "what explains the job losses during the recession?" The answer provided by this paper is that mortgage supply shocks mattered, though moderately. This suggests that other factors, such as the decline in household net worth (Mian and Sufi 2014) or increase in uncertainty (Baker et al. 2016) may explain the bulk of the job losses in the recession.

Credit supply shocks to *firms* may have also been an important contributor, though evidence is mixed, with Chodorow-Reich (2014) finding that credit shocks explain between one-fifth and one-third of aggregate employment losses in the year after Lehman's bankruptcy. However, for the smaller corporates taking out small business loans Greenstone et al. (2015) find that credit shocks help explain declines in borrowing, but led to only small overall employment effects. Duygan-Bump et al. (2015) also find that employment fell more in small firms in industries with high external financial dependence. They conclude that the small firm-high external financial dependence channel may explain about 8% of the rise in the aggregate unemployment rate, so overall the channel they identify may have had moderate aggregate implications as well.

5.5 Robustness

I test for the validity and interpretation of the main results of the paper along several dimensions. As discussed, a concern is that lenders with below-average supply systematically located in counties with below-average employment shocks during the boom – perhaps risky lenders moved to risky counties during the boom years. I measure the credit supply instrument as in equation 2, with the same lender shocks during the recession ϕ_b, but this time using 2000-2002 market shares (instead of 2005-2007 as in the baseline).

$$Nonlocal\ Lending\ Shock_i^{2000-2002\ shares} = \sum_B Share_{i,b}^{2000-2002} \phi_b \tag{7}$$

Figure 8 plots the baseline credit supply instrument measure against the instrument measured with 2000-2002 shares; the R-squared is close to 64 percent. Table 12 reports 2SLS results based on county exposure to lender shocks, with the exposure measured in 2000-2002. For identification, the important aspect is the point estimates are very similar, which is evidence that β^j are estimated consistently for different models j. The point estimates are indeed similar, though standard errors tend to be higher. For example, β is .087 in the total employment model (Column 3) while it is 0.114 in the baseline reported in Table 9, well within one standard error. The estimates are noisier – in the baseline, the first-stage F statistic was 43.83 whereas in this specification it is 20.10 – as is expected, due to the noise in measuring lender location in the early 2000s rather than immediately prior to the crisis.

I also run 'placebo' tests on the first and second stage equations. First, I regress yearly changes between mortgage credit (2000-2013) at the county-level on the 2007-2010 nonlocal lending shock and all the county controls used in the baseline specification. Figure 9 plots the coefficient estimates and associated 95 percent confidence intervals on a year-by-year basis. The mortgage credit shock helps explain credit changes over 2007-2008 and 2008-2009 only, and not during any of the prerecession years.[26] Second, I repeat the main 2SLS elasticity estimates, holding the right-hand side constant, but instead measuring left-hand side variables (e.g. employment changes) over the last two recessions: i) 1990-1992, during which the unemployment rate increased from 5.6 to 7.5 percent; and ii) 2000-2003, during which the unemployment rate increased from 4 percent (lowest since 1970) to 6 percent in 2003. Table 13 reports elasticity estimates for construction and total private employment. If coefficient estimates are positive and significant, that would indicate counties with below-average supply during the Great Recession tend to experience below-average employment shocks during other recessions, possibly for other unobserved characteristics of localities. However, the estimates are not significant, except for changes in total private employment over 1990-1992, though in this case the coefficient estimate has the opposite sign (negative rather than positive).

In the baseline results of the paper, I did not include institutions that filed for bankruptcy (and were not acquired by another lender), because the portion of lending changes that is nonlocal cannot be plausibly isolated for these lenders, since lending for these institutions fell by 100% everywhere (there is no variation across localities). This is a conservative choice. The inclusion of these lenders might lead to biased elasticity estimates. On the other hand, their exclusion likely decreases the statistical power of the estimation approach. I add to the sample the ten largest multimarket lenders who failed over 2005-2010.[27] Table 14 reports two stage least squares estimates when the credit supply instrument includes these large failed lenders. Their addition leads to a small increase in the first-stage F statistic. Moreover, the second stage estimates are very similar to the baseline. Some are a bit higher and some a

[26]Making a similar coefficient plot using a different dependent variable (e.g. total private employment) yields coefficient estimates which are not significant. The reason is there are efficiency gains with lumping the recession years into a single cross-section. Results available upon request.

[27]American Home Mortgage, New Century Financial, IndyMac, Fremont Investment, WMC Mortgage, Lehman, Ameriquest, Option One, First Magnus, and Taylor, Bean, & Whitaker Mortgage.

bit smaller, though all within one standard error of the baseline estimates.

I also check whether coefficient estimates are statistically different when adding additional controls. In particular, I add squared and cubed terms of some of the most important drivers of the housing boom and bust identified in the literature: the runup in home prices over 2003-2006, 2006 debt-to-income, and the fraction of borrowers in a county with Equifax Risk Score 3.0 less than 620. Table 15 reports the main regressions of the paper (with region fixed effects), this time including as additional explanatory variables the squared and cubed prerecession terms of these three variables. The results are essentially identical, ameliorating concern about omitted variable bias. The total private employment coefficient estimate is 0.091, compared with 0.114 in the baseline.

Finally, I show that the results in the paper are robust to controlling for realized declines in small business lending over 2007-2010, which I obtain from the Community Reinvestment Act dataset. I average the flow of new business originations over 2008-2010, and compute percent changes with respect to 2007. Table 16 shows that controlling for the change in small business lending does not affect the main results of the paper. This is evidence that the mortgage credit shock discussed in this paper is carefully identified, and pertains specifically to changes in the availability of mortgage credit. The total private employment coefficient estimate is 0.111, compared with 0.114 in the baseline. Part of the reason why the two channels are distinct is that the exposure of localities to small business and mortgage lenders is only weakly correlated. In other words, the small business lenders to a locality are often not the same as the mortgage lenders. Figure 10 plots HMDA shares against CRA shares for the top 4 banks; they are only weakly correlated.

6 Conclusion

One of the leading narratives of the Great Recession is the credit crunch view – disruptions in financial markets limited the supply of new credit, which reduced the spending capacity of households and firms and lowered aggregate demand and employment, as discussed in prominent models of the Great Recession (Eggertsson and Krugman 2012; Guerrieri and Lorenzoni 2017; Midrigan and Philippon 2016). This paper contributes to this literature by empirically quantifying the employment effects of changes in mortgage credit supply. The emphasis on mortgages complements existing research the majority of which focuses on corporate credit supply shocks (Chodorow-Reich 2014; Greenstone et al. 2015; Duygan-Bump et al. 2015).

To do so, I construct a county level mortgage credit supply instrument, which exploits two sources of heterogeneity: differences in the extent to which lenders cut supply in the Great Recession for nonlocal reasons, and variation in the intensity of county-lender relations coming into the recession. I then estimate the effect of changes in mortgage supply on employment, net of other possibly confounding factors affecting spending during the recession.

By quantifying the effects of mortgage supply reductions, this paper adds nuance to the debate on the drivers of the job losses during the Great Recession. Overall, the bottom line is that mortgage supply shocks mattered for employment, though only moderately so. Declines in mortgage supply caused declines in local real estate activity – in residential permits, house prices, and construction employment, for example – but the evidence does not suggest there were large spillover effects in other, broader employment categories. A partial equilibrium aggregation exercise, based on the estimated local elasticity of total private employment with respect to mortgage supply, indicates that the reduction in mortgage supply could explain about 13 percent of the employment losses in the Great Recession, or close to 1 million of the jobs lost. In other words, the reduction in mortgage supply likely aggravated the job losses to a meaningful extent. But, other factors – the decline in household net worth, increase in uncertainty, or credit supply reductions to firms – together likely explain the bulk of the job losses in the recession, particularly in sectors less directly linked to real estate.

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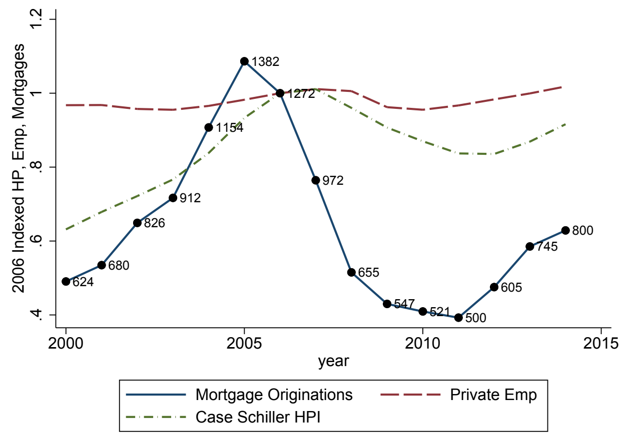
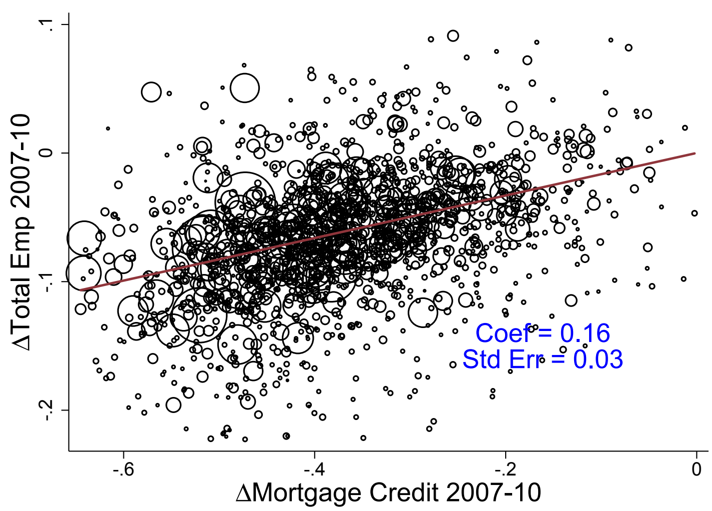
Figure 1: National Trends in Employment, House Prices, and Mortgage Originations



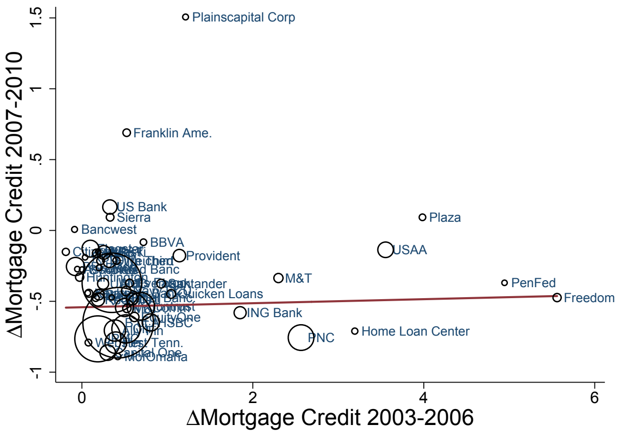
Mortgage originations are defined as the dollar value (in trillions) of originations for 1-4 residential loans for home purchase and improvement. Source: HMDA.

Figure 2: County Level Changes in Employment against Changes in Mortgage Credit Issuance, 2007-2010



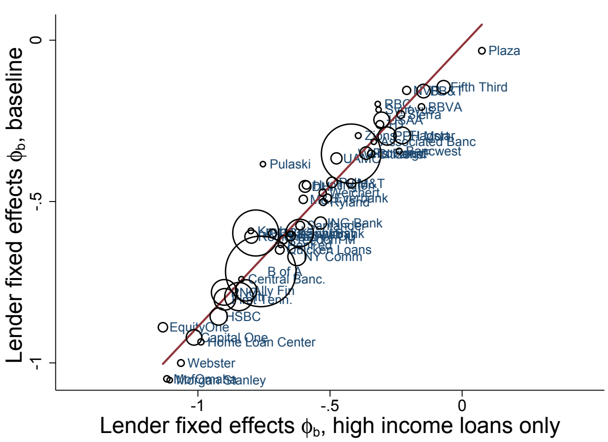
The figure plots changes in total private employment (y-axis) against changes in mortgage credit issuance (x-axis) over 2007-2010 at the county level for locations with over 15,000 housing units in the 2000 Census. The figure shows the linear coefficient estimate when regressing changes in employment on changes in mortgage credit issuance. Observations weighted by housing units in 2000 Census. Standard errors clustered at the division level.

Figure 3: Credit Changes 2007-2010 Versus Changes in 2003-2006



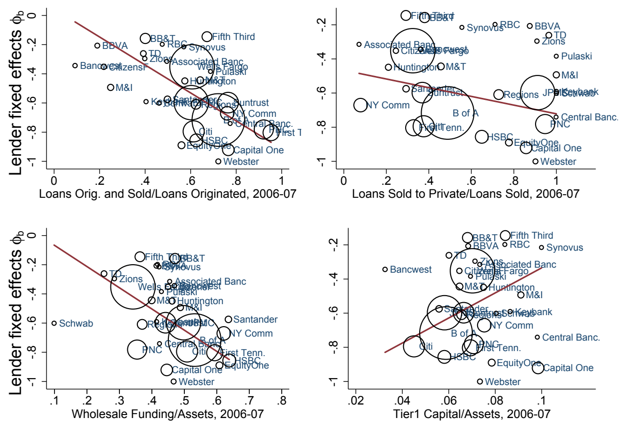
The figure plots changes in mortgage credit over 2007-2010 versus changes in mortgage credit over 2003-2006 for the large multimarket lenders in the sample.

Figure 4: Lender Fixed Effects Estimates in Baseline vs Only High Income Loan Specification



The figure plots lender fixed effects (equation 1) in the baseline (y-axis) against a specification that uses only high-income loans to estimate equation 1. Observations are weighted by the 2007 dollar value of mortgage originations. Outliers (5% upper tail) removed.

Figure 5: Funding Fragility and Lender Supply

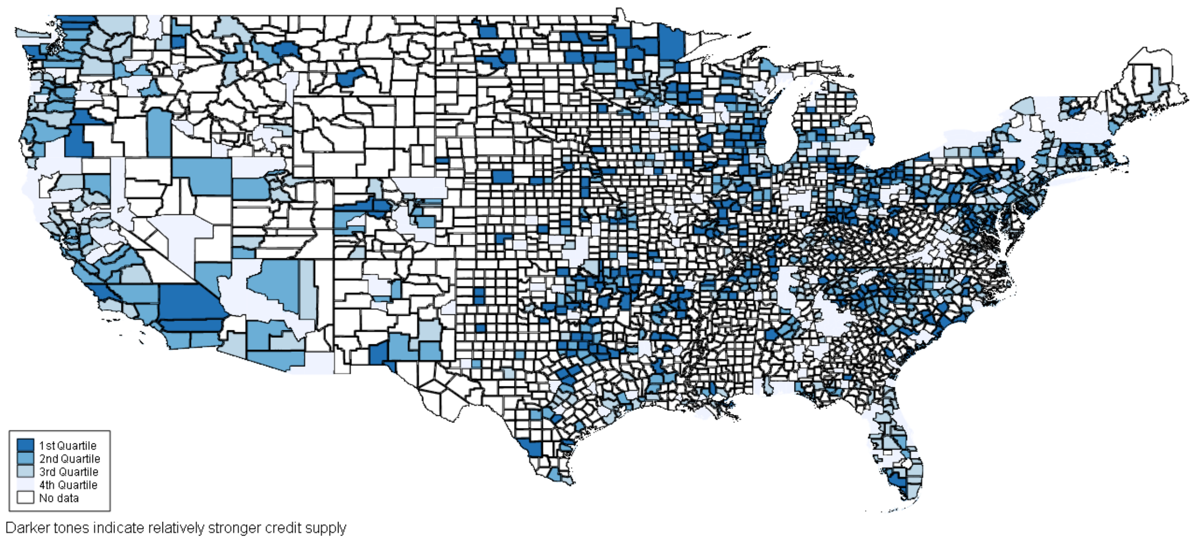


The variable on the y-axis measures differences in lender supply over 2007-2010, ϕ_b from equation 1. Variables on the x-axis are different measures of funding fragility over 2006-2007: ratio of mortgages originated and sold to total mortgages originated (top left); loans sold to private investors to total sales (top right); wholesale funding to assets (bottom left); and Tier 1 capital to assets (bottom right). Observations weighted by mortgage originations in 2007. The banks in the sample are large multimarket lenders located in at least 100 counties and with originations in excess of $1 billion in 2007. Outliers (5% upper tail) removed.

Figure 6: Persistent Market Shares

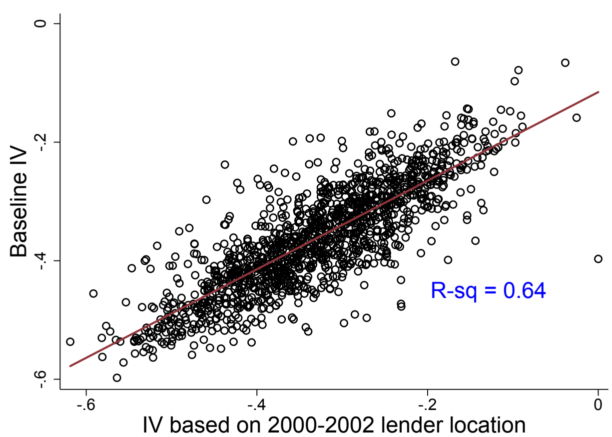
The left panel plots county-lender HMDA market shares in 2007 (y-axis) against market shares in 2005 (x-axis). The right panel plots county-lender HMDA market shares in 2007 (y-axis) against market shares in 2000 (x-axis). Lenders in the sample were located in at least 100 counties, issued over $1 billion in mortgage originations in 2007, and did not fail during the crisis. Counties in the sample had over 15,000 housing units in the 2000 Census.

Figure 7: Nonlocal Lending Shock



The map plots the residual variation in the credit supply instrument (the nonlocal lending shock) after regressing the credit supply instrument on the county controls used throughout the paper and defined in Table 2. The instrument is defined in equation 2. The map sorts the nonlocal lending shock into quartiles for counties in the sample. Darker tones indicate relatively stronger supply. Missing observations left blank (in white).

Figure 8: Nonlocal Lending Shock using 2000-2002 Market Shares



This figure plots the baseline credit supply instrument (nonlocal lending shock) on the y-axis, against the credit supply instrument which measures lender location over 2000-2002 in the x-axis. The baseline instrument measures lender location using 2005-2007 county-lender market shares as defined in equation 2.

Figure 9: Regressing Yearly Mortgage Credit Changes on Nonlocal Lending Shock

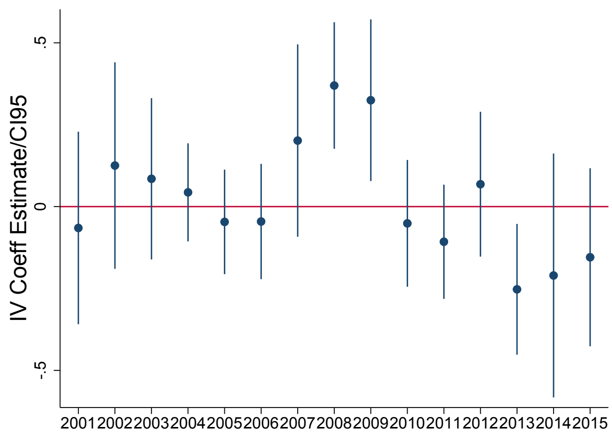
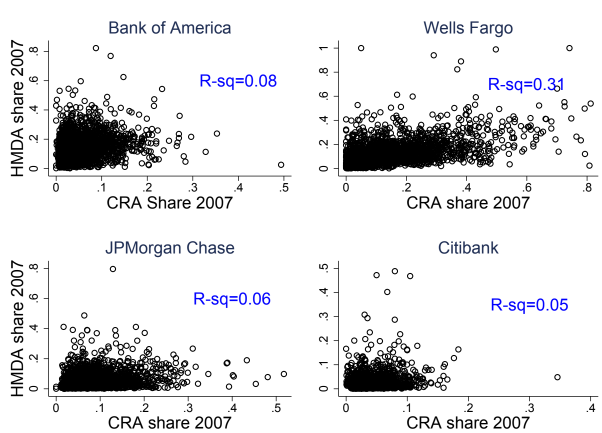


Figure shows coefficient estimates (ρ_t) and 95 percent confidence intervals when regressing yearly mortgage credit changes at the county-level on the nonlocal lending shock NLS_i and the other controls used in the baseline specification: $\Delta Credit_{i,t} = \rho_t NLS_i + \gamma X_i + \upsilon_i$ for $t = 2001, 2002, ...2014$

Figure 10: County-Lender Market Shares in HMDA and CRA



The figure plots mortgage 2007 market shares from HMDA (y-axis) against 2007 small business loan market shares from the CRA (x-axis) for each of the big-4 lenders and for localities with over 15,000 housing units in the 2000 Decennial Census.

Table 1: County Summary Statistics

Dependent Variables, 2007-2010 percent changes	Mean	SD	p10	Median	p90	N
Δ Private Emp	-0.065	0.047	-0.125	-0.063	-0.009	1013
Δ Construction Emp	-0.240	0.142	-0.413	-0.247	-0.059	987
Δ Finance Emp	-0.081	0.088	-0.189	-0.084	0.023	1012
Δ Other Emp	-0.048	0.049	-0.109	-0.047	0.011	1012
Δ Nontradable Emp	-0.045	0.063	-0.117	-0.051	0.034	1010
Δ Home Prices	-0.141	0.105	-0.290	-0.128	-0.013	1008
Δ Home Permits	-0.465	0.142	-0.645	-0.477	-0.267	932
Δ Delinquency +90 Days	0.040	0.025	0.018	0.032	0.071	1012
Δ Foreclosures	0.015	0.013	0.006	0.012	0.027	1013
Δ Mortgage Credit	-0.395	0.111	-0.530	-0.404	-0.248	1009
Prerecession Characteristics						
# Housing Units (thousands), 2000	94.599	179.490	17.803	41.248	216.948	1030
% White Pop, 2000	0.864	0.124	0.698	0.909	0.977	1030
% Educ ≥ College, 2000	0.216	0.089	0.121	0.196	0.341	1030
$HH Median Income (thousands), 2000	41.528	9.662	31.258	39.557	55.389	1030
$Home Value (thousands), 2000	108.300	47.862	66.600	95.250	161.750	1030
Δ 2003-2006 Home Prices	0.250	0.181	0.063	0.203	0.516	1030
% Owner-Occupied Loans, 2003-2006	0.849	0.095	0.736	0.878	0.928	1030
% GSE-securitized Loans, 2003-2006	0.665	0.133	0.498	0.699	0.786	1030
% Nonconventional Loans, 2003-2006	0.184	0.111	0.050	0.172	0.324	1030
Δ 2003-2006 #Lenders	0.419	0.296	0.111	0.364	0.797	1030
% Risk Score ≤ 620, 2006	0.270	0.082	0.174	0.257	0.392	1030
Median Risk Score, 2006	709.466	32.626	659.250	717.000	746.000	1030
HH Debt to Income, 2006	1.782	0.596	1.171	1.638	2.603	1030
Herfindahl Index, 2006	0.062	0.026	0.038	0.056	0.095	1030
Construction Share of Emp, 2006	0.122	0.045	0.075	0.113	0.184	1030
Tradable Share of Emp, 2006	0.135	0.082	0.044	0.120	0.247	1030
Unemployment Rate, 2007	4.749	1.410	3.300	4.500	6.400	1030
$Mortgage Credit (millions), 2007	905.114	2219.941	59.139	284.334	2185.790	1030
# Employed (thousands), 2007	97.738	214.502	11.192	35.106	229.155	1030

The table provides summary statistics for localities with over $15,000$ households in the 2000 Decennial Census. The change in delinquency and foreclosure rates is in percentage points. For stocks (e.g. home prices), changes are taken between 2010Q4 and 2007Q4. For flows (e.g. mortgage originations), changes are taken between the average flow over 2008-2010 and the value in 2007.

Table 2: Data Definitions

Variable	*Definition*	*Source*
Dependent Variables, 2007-2010 percent changes		
Mortgage Credit	By county-year, the dollar amount of originations for 1-4 residential loans for home purchase and improvement.	HMDA
Δ Credit	Percent change in average mortgage credit over 2008-2010 with respect to 2007	HMDA
Δ Residential Permits	Percent change in average permits over 2008-2010 with respect to 2007	Census
Δ House Prices	Percent change in house prices from 2007Q4 to 2010Q4.	CoreLogic HPI
Δ Emp^j	Percent change in employment category j from 2007Q4 to 2010Q4	QCEW
Δ Delinquency Rates	Percentage point change in fraction of 90+ delinquent properties from 2007 to 2010	Black Knight McDash
Δ Foreclosures Rates	Percentage point change in fraction of foreclosed properties from 2007 to 2010	Black Knight McDash
Prerecession Characteristics		
Level Home Prices	Log level median house price	2000 Census
Household Income	Median	2000 Census
White population	Fraction of population identified as white	2000 Census
College population	Fraction of population with a college degree or more	2000 Census
Risk Score 3.0	Median	2006 FRBNY Consumer Credit Panel/Equifax
Subprime	Fraction of households in a county with Risk Score less than 620	2006 FRBNY Consumer Credit Panel/Equifax
Household Debt-to-Income	Median household debt-to-income	2006 FRBNY Consumer Credit Panel/Equifax
Nonconventional Loans	One minus the fraction of loans issued over 2003-2006 identified as conventional loans	Black Knight McDash
GSE-securitized Loans	Fraction of loans issued over 2003-2006 insured by GNMA, FNMA, or FHLMC	Black Knight McDash
Owner-Occupied Loans	Fraction of mortgages over 2003-2006 identified as owner-occupied	HMDA
Δ # Lenders	Growth in the number of lenders per county over 2003-2006	HMDA
Δ House Prices	Growth in house prices over 2003Q4-2006Q4	CoreLogic HPI
Tradable	Tradable share of employment, as defined in Mian and Sufi (2014)	2006 CBP
Construction	Construction share of employment, as defined in Mian and Sufi (2014)	2006 CBP
Herfindahl Index	Sum of squared market shares across lenders in county	2006 HMDA
Unemp Rate	Unemployment Rate	2007 BLS LAU
Level Employment	Log level of employed workers	2007 QCEW
Level Mortgage Credit	Log level of mortgage originations	2007 HMDA

This table provides definitions and sources for the data used throughout the paper. HMDA: Home Mortgage Disclosure Act; CBP: County Business Patterns; QCEW: Quarterly Census of Employment and Wages; BLS: Bureau of Labor Statistics Local Area Unemployment Statistics.

Table 3: Lender Summary Statistics

	Mean	SD	p10	Median	p90	N
Δ Mortgage Credit 2007-2010	-0.35	0.38	-0.76	-0.37	0.01	57
#Counties 2007	484.02	473.21	122.00	274.00	1117.00	57
Mortgage Credit 2007 (billions)	11.97	30.45	1.08	2.55	24.11	57
Sales/Originations 2006-2007	0.68	0.25	0.36	0.71	0.99	57
Private Loan Sales/Sales 2006-2007	0.66	0.34	0.18	0.73	1.00	57
Wholesale Funding/Assets 2006-2007	0.44	0.11	0.34	0.44	0.61	33
Tier 1 Capital/Assets 2006-2007	0.07	0.01	0.06	0.07	0.09	33

This table provides summary statistics for the lenders in the sample, which are large multimarket lenders located in at least 100 counties and with originations in excess of $1 billion in 2007.

Table 4: Lender Rankings by Percent Changes in Mortgage Originations and Lender Fixed Effects Estimates

Lender	ΔOriginations, 2007-2010	Ranking by ΔOriginations	Ranking by Baseline Lender Fixed Effects Estimates	Originations, $billions 2007
US Bank	.17	3	3	7.45
Flagstar	-.13	8	14	10.37
USAA	-.14	9	12	8.86
BB&T	-.15	12	7	6.84
Provident	-.18	14	19	5.64
Fifth Third	-.21	18	5	6.41
PPH Mort	-.25	19	16	12.11
Wells Fargo	-.37	27	20	129.73
UAMC	-.38	30	22	4.52
Navy FCU	-.43	31	39	3.3
Pulte	-.45	35	24	4.05
DHI	-.48	39	27	5.09
Regions	-.49	40	40	6.3
Suntrust	-.53	41	36	27.86
NY Comm	-.54	42	44	12.01
ING Bank	-.58	44	32	5.34
EquityOne	-.61	45	52	3.18
HSBC	-.65	46	51	10.89
Bank of America	-.65	47	45	182.57
Citibank	-.69	48	49	29.27
Ally Fin	-.71	49	47	16.63
PNC	-.76	51	48	24.11
JPMC	-.76	52	35	77.69
First Tennessee	-.79	54	50	17.05
Capital One	-.86	55	53	8.82

The table shows summary statistics for the 25 largest lenders in the sample (large nonfailed multimarket lenders, see Section 2). Column 2 ranks lenders by decline in new mortgage lending. Column 3 ranks lenders by baseline lender fixed effects estimates ϕ_b from equation 1.

Table 5: Funding Fragility and Differences in Lender Supply

	Dependent variable: ϕ^b			
	(1)	(2)	(3)	(4)
	Coef./SE	Coef./SE	Coef./SE	Coef./SE
Wholesale Debt/Assets 2006-2007	-0.494***	-0.406***	-0.431***	-0.430***
	(0.093)	(0.104)	(0.114)	(0.141)
Loan Sales/Originations 2006-2007	-0.584***	-0.629***	-0.572***	-0.542***
	(0.130)	(0.129)	(0.164)	(0.147)
Private Loan Sales/Originations 2006-2007	-0.311***	-0.302***	-0.285***	-0.540***
	(0.097)	(0.094)	(0.100)	(0.143)
Tier1 Capital 2006-2007		0.216	0.208	0.219
		(0.128)	(0.130)	(0.143)
Δ Mortgage Credit 2003-2006			-0.065	0.048
			(0.114)	(0.141)
Weighted	Yes	Yes	Yes	No
N	32	32	32	32
R-squared	0.74	0.77	0.77	0.59
Adj R-squared	0.71	0.73	0.72	0.51

The dependent variable measures differences in lender supply over 2007-2010, ϕ_b from equation 1. The explanatory variables measure the extent to which banks relied on fragile funding sources over 2005-2007, and credit growth over 2003-2006. Standard errors are in parentheses. Banks in the sample are large multimarket lenders as described in Section 2. All variables are standardized. 1% upper tail of lender fixed effects winsorized. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 6: Mortgage Market Shares are Highly Persistent Year-on-Year

	Dependent variable: County-Lender Market Shares 2007			
		Bottom credit risk quartile	*Top credit risk quartile*	*County FE*
	Coef./SE	Coef./SE	Coef./SE	Coef./SE
2005 Market Shares	0.918***	0.922***	0.920***	0.916***
	(0.00)	(0.01)	(0.01)	(0.00)
County FE	No	No	No	Yes
R-squared	0.92	0.89	0.93	0.92
Observations	33658	8169	8071	33658

This table show results from regressing 2007 county-lender market shares on 2005 county-lender market shares. Column 2 restricts the sample to the low Equifax Risk Score 3.0 quartile, Column 3 to the high Risk Score quartile, and Column 4 includes county fixed effects. The lenders in the sample are large multimarket lenders located in at least 100 counties and with originations in excess of $1 billion in 2007. Counties in the sample had over 15,000 households in the 2000 Decennial Census. Standard errors clustered at the county level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 7: First Stage Results

	Dependent variable: Δ Mortgage Credit 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Nonlocal Lending Shock	0.479*** (0.11)	0.526*** (0.08)	0.430*** (0.09)	0.247*** (0.07)
All other controls	Yes	Yes	Yes	Yes
R-squared	0.56	0.62	0.67	0.76
Adj. R-squared	0.56	0.62	0.66	0.75
Kleibergen-Paap F stat	20.02	42.98	24.41	13.95
Observations	1009	1009	1009	1009

This table shows first-stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Dependent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 8: Housing Elasticities with respect to Mortgage Supply

	Dependent variables 2007-2010:			
	Δ Permits Coef./SE	Δ Home Price Coef./SE	Δ Delinq. Rate Coef./SE	Δ Foreclosure Rate Coef./SE
Δ Mortgage Credit 2007-2010	0.824*** (0.07)	0.757*** (0.15)	-0.143*** (0.05)	-0.091*** (0.04)
All other controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
R-squared	0.44	0.75	0.77	0.56
Kleibergen-Paap F stat	45.54	40.06	50.06	52.36
Observations	919	991	997	998

This table shows the effects of changes in mortgage credit, when instrumented using the nonlocal lending shock, on changes in local outcomes for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include region fixed effects and all characteristics of localities used throughout the paper defined in Table 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Dependent variable outliers (1 percent of each tail) are dropped. Standard errors are clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 9: Employment Elasticities with respect to Mortgage Supply

	Dependent variables 2007-2010:				
	Δ Constr. Emp Coef./SE	Δ Fin Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.381***	0.440***	0.114***	0.041	0.066
	(0.08)	(0.07)	(0.04)	(0.05)	(0.10)
All other controls	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.63	0.16	0.53	0.41	0.41
Kleibergen-Paap F stat	43.32	44.29	43.83	43.50	45.42
Observations	967	991	992	991	989

This table shows the effects of changes in mortgage credit, when instrumented using the nonlocal lending shock, on changes in local outcomes for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include region fixed effects and all characteristics of localities used throughout the paper defined in Table 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Dependent variable outliers (1 percent of each tail) are dropped. Standard errors are clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 10: Elasticity of Construction Employment with Housing Supply Interaction

	Dependent variables 2007-2010:			
	Δ Constr. Emp Coef./SE	Δ Constr. Emp Coef./SE	Δ Permits Coef./SE	Δ Permits Coef./SE
Δ Mortgage Credit 2007-2010	0.332***	0.358***	0.882***	0.962***
	(0.09)	(0.10)	(0.13)	(0.15)
Δ Mortgage Credit 2007-10 × Elasticity		0.128***		0.205*
		(0.05)		(0.12)
All other controls	Yes	Yes	Yes	Yes
Kleibergen-Paap F stat	32.88	15.72	30.39	13.71
Observations	538	538	511	511

This table shows the effects of changes in mortgage credit over 2007-2010, interacted with the housing supply elasticity of Saiz (2010), on changes in construction employment and permit issuance during the recession. All regressions include region fixed effects and all other observed characteristics of localities used in the other tables in the paper (Table 2). The nonlocal lending shock measures the exposure of counties to lender shocks as defined in equation 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 11: OLS Estimation Results

	Dependent variables:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.706*** (0.09)	0.364*** (0.08)	0.160*** (0.01)	0.141*** (0.02)	0.131*** (0.02)
All other controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.44	0.63	0.54	0.44	0.42
Adj. R-squared	0.43	0.63	0.52	0.43	0.40
Observations	919	967	992	991	989

This table shows that the OLS coefficients when regressing changes in outcome variables (e.g. home permits) on changes in mortgage credit at the county-level over 2007-2010 while controlling for all prerecession county characteristics listed in Table 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 12: Elasticities With IV Constructed Using 2000-2002 Shares

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.616*** (0.12)	0.165 (0.18)	0.087 (0.06)	0.017 (0.07)	-0.046 (0.14)
All other controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.44	0.62	0.52	0.40	0.37
Kleibergen-Paap F stat	20.69	19.92	20.10	20.96	21.69
Observations	919	967	992	991	989

This table shows the effects of changes in mortgage credit over 2007-2010, when instrumented using the nonlocal lending shock based on 2000-2002 market shares (as opposed to the baseline measure which uses 2005-2007 shares); see equation 7. All regressions include region fixed effects and all other observed characteristics of localities used in the other tables in the paper (Table 2). The nonlocal lending shock measures the exposure of counties to lender shocks as defined in equation 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 13: ‘Placebo’ Regressions

	Δ Total 90-92 Coef./SE	Δ Total 00-03 Coef./SE	Δ Constr 90-92 Coef./SE	Δ Constr 00-03 Coef./SE
Δ Mortgage Credit 2007-2010	-0.107*** (0.03)	0.054 (0.08)	-0.043 (0.12)	0.162 (0.15)
All other controls	Yes	Yes	Yes	Yes
Observations	1009	1009	968	968

This table reports results from ‘placebo’ regressions over the previous two recessions. The dependent variables are in percent change over 1990-1992 and 2000-2003. All regressions include region fixed effects and all other observed characteristics of localities used in the other tables in the paper (Table 2). Observations weighted by 1990 payrolls. Decennial Census. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 14: Elasticity Estimates Including Failed Lenders

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.931*** (0.10)	0.372*** (0.10)	0.096** (0.04)	0.028 (0.06)	0.065 (0.11)
All other controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.43	0.63	0.52	0.40	0.41
Kleibergen-Paap F stat	51.43	44.39	44.90	44.43	46.51
Observations	919	967	992	991	989

This table shows the effects of changes in mortgage credit over 2007-2010, when instrumented using the nonlocal lending shock, including large institutions who filed for bankruptcy over 2005-2010: American Home Mortgage, New Century Financial, IndyMac, Fremont Investment, WMC Mortgage, Lehman, Ameriquest, Option One, First Magnus, and Taylor, Bean, & Whitaker Mortgage. All equations include region fixed effects and all other observed characteristics of localities used in the other tables in the paper (Table 2). The nonlocal lending shock measures the exposure of counties to lender shocks as defined in equation 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 15: Elasticity Estimates with Additional Controls

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.859*** (0.13)	0.400*** (0.09)	0.091** (0.04)	0.010 (0.06)	0.051 (0.10)
All other controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.49	0.64	0.53	0.40	0.43
Kleibergen-Paap F stat	29.57	32.40	32.76	32.04	33.46
Observations	919	967	992	991	989

This table shows the effects of changes in mortgage credit over 2007-2010, when instrumented using the nonlocal lending shock, on local outcomes. These regressions include squared and cubed terms for household debt-to-income, the local fraction of subprime borrowers, and the runup in home prices over 2003-2006. All equations include region fixed effects and all other observed characteristics of localities used in the other tables in the paper (Table 2). The nonlocal lending shock measures the exposure of counties to lender shocks as defined in equation 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 16: Elasticity Estimates Including Changes in Small Business Lending (CRA)

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.821*** (0.08)	0.376*** (0.08)	0.111*** (0.04)	0.037 (0.05)	0.063 (0.10)
All other controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.44	0.64	0.53	0.42	0.41
Kleibergen-Paap F stat	52.40	47.94	49.89	49.50	51.50
Observations	919	967	992	991	989

This table shows the effects of changes in mortgage credit over 2007-2010, when instrumented using the nonlocal lending shock, on local outcomes. I include changes in small business lending over 2007-2010 obtained from the Community Reinvestment Act. All equations include region fixed effects and all other observed characteristics of localities used in the other tables in the paper (Table 2). The nonlocal lending shock measures the exposure of counties to lender shocks as defined in equation 2. Observations weighted by the number of housing units in the 2000 Decennial Census. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Employment in the Great Recession: How Important Were Household Credit Supply Shocks?

Online Appendix

The appendix consists of tables complementing the main results in the paper. Tables 1-9 report second stage results for each of the main dependent variables in the paper, for specifications with no spatial fixed effects, region, division, and state fixed effects (Columns 1-4, respectively).

In the paper, changes in mortgage credit issuance during the recession $\Delta Credit$ are defined as the percent change in the average real dollar value of mortgage originations over 2008-2010 with respect to their value in 2007. Estimates are robust to alternative definitions, such as using the average real dollar flow of originations over 2005-2007 as the base (Table 10) or using the percent change in the number (rather than the real dollar value) of mortgage originations between 2007-2010 (Table 11). In the baseline regressions, observations are weighted by population. Table 12 shows results from unweighted regressions, for close to the largest 500 counties in the sample, where the number of households (from the 2000 Decennial Census) exceeds 40,000. Finally, Table 13 shows estimates when clustering standard errors at the commuting zone level.

List of Tables

Table 1: Elasticity of Residential Permits with respect to Mortgage Supply

	Dependent variable: Δ Permits 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	0.561***	0.824***	0.845***	1.098***
	(0.11)	(0.07)	(0.09)	(0.20)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	21.18	45.54	26.17	10.46
p-value K-P LM test	0.01	0.01	0.01	0.03
Observations	919	919	919	919

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 2: Elasticity of Home Prices with respect to Mortgage Supply

	Dependent variable: Δ Home Price 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	0.673***	0.757***	0.828***	0.789***
	(0.16)	(0.15)	(0.17)	(0.16)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	18.42	40.06	21.77	13.10
p-value K-P LM test	0.02	0.01	0.02	0.02
Observations	991	991	991	991

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 3: Elasticity of Delinquency Rates with respect to Mortgage Supply

	Dependent variable: Δ Delinq. Rate 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	-0.187***	-0.143***	-0.141**	-0.168***
	(0.05)	(0.05)	(0.06)	(0.06)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	22.99	50.06	25.99	14.66
p-value K-P LM test	0.02	0.01	0.01	0.02
Observations	997	997	997	997

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 4: Elasticity of Foreclosure Rates with respect to Mortgage Supply

	Dependent variable: Δ Foreclosure Rate 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	-0.118***	-0.091***	-0.084*	-0.068**
	(0.04)	(0.04)	(0.05)	(0.03)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	23.52	52.36	29.50	15.50
p-value K-P LM test	0.02	0.01	0.01	0.02
Observations	998	998	998	998

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 5: Elasticity of Construction Employment with respect to Mortgage Supply

	Dependent variable: Δ Constr. Emp 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	0.209	0.381***	0.217	0.672***
	(0.15)	(0.08)	(0.15)	(0.22)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	20.33	43.32	26.29	16.35
p-value K-P LM test	0.02	0.01	0.01	0.02
Observations	967	967	967	967

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 6: Elasticity of Financial Employment with respect to Mortgage Supply

	Dependent variable: Δ Fin Emp 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	0.435***	0.440***	0.478***	0.893***
	(0.08)	(0.07)	(0.09)	(0.19)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	20.45	44.29	24.79	13.47
p-value K-P LM test	0.02	0.01	0.01	0.02
Observations	991	991	991	991

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 7: Elasticity of Private Employment with respect to Mortgage Supply

	Dependent variable: Δ Total Emp 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	0.081	0.114***	0.068	0.083
	(0.05)	(0.04)	(0.06)	(0.10)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	19.92	43.83	24.56	14.95
p-value K-P LM test	0.02	0.01	0.01	0.02
Observations	992	992	992	992

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 8: Elasticity of Other Employment with respect to Mortgage Supply

	Dependent variable: Δ Other Emp 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	0.021	0.041	0.009	-0.048
	(0.06)	(0.05)	(0.07)	(0.13)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	19.91	43.50	24.72	14.17
p-value K-P LM test	0.02	0.01	0.01	0.02
Observations	991	991	991	991

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 9: Elasticity of Nontradable Employment with respect to Mortgage Supply

	Dependent variable: Δ Nontr. Emp 2007-2010			
	No FE Coef./SE	*Region FE* Coef./SE	*Division FE* Coef./SE	*State FE* Coef./SE
Δ Mortgage Credit 2007-2010	-0.010	0.066	0.053	0.183
	(0.15)	(0.10)	(0.13)	(0.11)
All other controls	Yes	Yes	Yes	Yes
K-P F stat	20.49	45.42	25.52	14.28
p-value K-P LM test	0.02	0.01	0.01	0.02
Observations	989	989	989	989

This table shows first stage results from regressing changes in mortgage credit issuance over 2007-2010 on the credit supply instrument (the nonlocal lending shock) for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Dpendent variable outliers (1 percent of each tail) are dropped. Standard errors clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 10: Estimates When Defining $\Delta Credit$ Using 2005-2007 as the Base Period

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.809***	0.406***	0.123***	0.050	0.073
	(0.11)	(0.09)	(0.04)	(0.05)	(0.10)
All other controls	Yes	Yes	Yes	Yes	Yes
K-P F stat	21.11	18.79	19.99	19.92	19.55
p-value K-P LM test	0.01	0.02	0.02	0.02	0.02
Observations	917	964	989	988	986

This table shows the effects of changes in mortgage credit, when instrumented using the nonlocal lending shock, on changes in local outcomes for counties with over 15,000 housing units in the 2000 Census. $\Delta Credit$ measured as the change in the real dollar value of morgage originations over 2008-2010 relative to the value in 2005-2007. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include region fixed effects and all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Outliers (1 percent of each tail) are dropped. Standard errors are clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 11: Estimates When Defining $\Delta Credit$ Using Changes in the Number of Loans

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.855***	0.411***	0.123***	0.046	0.064
	(0.10)	(0.09)	(0.04)	(0.05)	(0.11)
All other controls	Yes	Yes	Yes	Yes	Yes
K-P F stat	66.29	62.70	69.67	68.60	72.04
p-value K-P LM test	0.01	0.01	0.01	0.01	0.01
Observations	918	967	993	991	990

This table shows the effects of changes in mortgage credit, when instrumented using the nonlocal lending shock, on changes in local outcomes for counties with over 15,000 housing units in the 2000 Census. $\Delta Credit$ measured as the change in the average number of originations over 2008-2010 relative to the 2007 number. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include region fixed effects and all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Outliers (1 percent of each tail) are dropped. Standard errors are clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 12: Estimates With No Population Weighting

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.808***	0.366***	0.110***	0.039	0.034
	(0.07)	(0.09)	(0.04)	(0.05)	(0.11)
All other controls	Yes	Yes	Yes	Yes	Yes
K-P F stat	38.46	50.21	50.94	51.08	50.96
p-value K-P LM test	0.01	0.01	0.01	0.01	0.01
Observations	483	505	515	516	514

This table shows the effects of changes in mortgage credit, when instrumented using the nonlocal lending shock, on changes in local outcomes for counties with over 40,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include region fixed effects and all characteristics of localities used throughout the paper defined in Table 3. Outliers (1 percent of each tail) are dropped. Standard errors are clustered at the division level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 13: Estimates with Standard Errors Clustered at Commuting Zone

	Dependent variables 2007-2010:				
	Δ Permits Coef./SE	Δ Constr. Emp Coef./SE	Δ Total Emp Coef./SE	Δ Other Emp Coef./SE	Δ Nontr. Emp Coef./SE
Δ Mortgage Credit 2007-2010	0.824***	0.381***	0.114**	0.041	0.066
	(0.21)	(0.11)	(0.04)	(0.05)	(0.08)
All other controls	Yes	Yes	Yes	Yes	Yes
K-P F stat	55.03	59.19	62.21	62.34	58.30
p-value K-P LM test	0.00	0.00	0.00	0.00	0.00
Observations	919	967	992	991	989

This table shows the effects of changes in mortgage credit, when instrumented using the nonlocal lending shock, on changes in local outcomes for counties with over 15,000 housing units in the 2000 Census. The nonlocal lending shock measures the exposure of counties to nonlocal lender shocks (see equation 2). All equations include region fixed effects and all characteristics of localities used throughout the paper defined in Table 3. Observations weighted by the number of housing units in the 2000 Decennial Census. Outliers (1 percent of each tail) are dropped. Standard errors are clustered at the commuting zone level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.